# LANDSLIDE FEATURES INTERPRETED BY NEURAL NETWORK METHOD USING A HIGH-RESOLUTION SATELLITE IMAGE AND DIGITAL TOPOGRAPHIC DATA

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**ABSTRACT:**

Landslides are natural phenomena for the dynamic balance of earth surface. Due to the frequent occurrences of Typhoons and earthquake activities in Taiwan, mass movements are common threatens to our lives. Moreover, it is a common practice for the agencies of water reservoirs in Taiwan to make a reconnaissance of the landslides of the watershed every 5 to 10 years for the purpose of conservation. It is found that the application of aerial photo-interpretation technique for this purpose has been recognized as an effective approach since 1970s. However, an efficient and automatic interpretation scheme has never been established. Therefore, two issues are to be resolved for creating a useful and timely landslide database, i.e. the consistency of the sub-datasets and the completeness of the coverage. As the manual interpretation and automatic recognition are compared, the former is a practical and operational method, but the result it derived is largely dependent on the professional background of interpretation operator.

In this paper, the interpretation knowledge is quantified into recognition criteria. Multi-source data, e.g. a Quickbird satellite image, DTM reduced from a LIDAR data, road and river vector data, are fused to construct the feature space for landslides analysis. Then, those features are used to recognize landslides by a multilayer perceptron (MLP) Neural Network Method. The extraction result is evaluated in comparison with the manual-interpretation result. The experiments indicate that the conducted method can assist landslide investigation efficiently and automatically. Moreover, the ANN method is better than some statistic classification methods, e.g. Maximum Likelihood method, due to its adaptability for multi-resource data and no predefined assumption.

## 1. INTRODUCTION

Landslides are natural phenomena for the dynamic balance of earth surface. The potential or intrinsic factors of landslide include geological and morphological factors and the external or triggering factors include earthquake, climate, hydrology, and human activities. When the geology is highly fractured and landforms are in high relief. In addition, the frequent earthquakes and heavy rainfalls are together imposing further stress to the earth to break the balance of the nature. And, thus, mass movements such as landslides, slumping, and mudflows take places.

### 1.1 Motivations

Moreover, it is a common practice for the agencies of water reservoirs in Taiwan to make a reconnaissance of the landslides of the watershed every 5 to 10 years for the purpose of conservation. It is found that the application of aerial photo-interpretation technique for this purpose has been recognized as an effective approach since 1970s. However, an efficient and automatic interpretation scheme has never been established. Therefore, two issues are to be resolved for creating a useful and timely landslide database, i.e. the consistency of the datasets and the completeness of the coverage. As the manual interpretation and automatic recognition are compared, the former is a practical and operational method, but the result it derived is largely dependent on the professional background of interpretation operator.

It is usually taking a long time to make a large-scale and real-time mapping of landslides after a torrential rainfall. The first general mapping of landslides in Taiwan was conducted by Soil and Water Conservation Bureau in 1982-1989 and a landslide map of Taiwan in a scale of 1/50,000~1/100,000 (COA, 1991). In 8 years of survey, there were more than 10 times of torrential rainfalls and 100 times of earthquakes and new balance of the nature took time and time again. In reality, to map all the landslides in one time is not feasible. And, it is understandable that the difficulties of obtaining a survey with completeness of a whole Taiwan coverage. It has been a common practice to interpret aerial photographs by visual inspection of an expert geologist. It is a time consuming task. Therefore, the purpose of this study is to implement the human rules and quantifies the criteria to install an automatic system by a back-propagation Neural Network Method.

### 1.2 Overview and References to related works

Landslides cause approximately 1000 deaths a year worldwide with a property damage of about US$4 billion, and pose serious threats to settlements and structures that support transportation, natural resource management and tourism. In many cases, over-expanded development and activities, such as slope cutting and deforestation, can sometimes increase the incidence of landslide disasters. Recent development in large metropolitan areas intrudes upon unstable terrain. This has thrown many urban communities into disarray, providing grim examples of the extreme disruption caused by ground failures (Singhroy & Mattar, 2000).

Aerial photography has been used extensively to characterize landslides and to produce landslide inventory maps, particularly because of their stereo viewing capability and high spatial resolution (Liu, 1985, Liu, 1987). However, the conventional photo-interpretation is a time-consuming and costly approach (Liu et al., 2001).

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Satellite imagery can also be used to collect data on the relevant parameters involved such as soils, geology, slope, geomorphology, land use, hydrology, rainfall, faults, etc. Multispectral images are used for the classification of lithology, vegetation, and land use, Stereo SPOT imagery is used in geo-morphological mapping or terrain classification (Liu, 1987; Wu et al., 1989; Liang, 1997; Liu, 1999; Hsu, 2002).

For landslide inventory mapping the size of the landslide features in relation to the ground resolution of the remote sensing data is very important. A typical landslide of 40000 $m^2$, for example, corresponds with 20x20 pixels on a SPOT Pan image and 10*10 pixels on SPOT multi-spectral images. This would be sufficient to identify a landslide that has a high contrast, with respect to its surroundings e.g. bare scarps within vegetated terrain, but it is insufficient for a proper analysis of the elements pertaining to the failure to establish characteristics and type of landslide. Imagery with sufficient spatial resolution and stereo capability such as SPOT or IRS can be used to make a general inventory of the past landslides. However, they are mostly not sufficiently detailed to map out all landslides (Hsiao et al., 2003). It is expected that in the future the Very High Resolution (VHR) imagery, such as from IKONOS-2, might be used successfully for landslide inventory (Westen, 2000). By using the criteria for visual interpretation, artificial intelligent of expert system and automatic procedures can be developed to improve the efficiency and accuracy of landslide mapping (Kojima et al., 2000, Liu et al., 2001).

Artificial Neural Networks (ANNs) have been used successfully in many applications such as pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control (Robert, 1990, Zurada, 1992). ANNs have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more traditional computational methods.

## 2. METHODOLOGY

### 2.1 Traditional landslide interpretation methods

Individual landslides are generally small and located in certain locations of a slope. Landslides occur in a large variety, depending on the type of movement such as (slide, topple, flow, fall, spread), the speed of movement (mm/year-m/sec), the material involved (rock, debris, soil), and the triggering mechanism (earthquake, rainfall, human interaction). Survey methods usually include ground survey, aerial or space-borne survey, or a combination.

Ground survey can be high accurate, but slow. When hazards take places, accessibility is low. Therefore, it is impossible to make the survey in near real-time or in a complete coverage after a torrential rainfall.

Photographic or image interpretation approach can be adopted and implemented manually, automatically, or semi-automatically. Manual interpretation requires well-trained geologist to delineate the landslides under a stereoscopic environment. The advantage of this approach is that individual landslide can be defined very clearly. However, the subject judgement is the disadvantage. Automatic classification of landslides is based on certain criteria and computing algorithms. The advantage for image classification is the objectiveness of the approach. In a real case, limitations are due to the spatial and spectral resolutions of the images. More than 50% of the rainfall-induced landslides in Taiwan are less than 50 m in length. Landslides of this scale are not readily identifiable using images of a pixel-size larger than 10 m. By pixel-wise classification, landslides can occupy only individual or just a few pixels without forming an outer shape of landslides. Moreover, commission and omission errors can further complicate the situation.

### 2.2 Interpretation Signatures

Key rules for this study are summarized from literatures, case studies, and expert experiences, as shown in Table 1.

| Key Rule | Contents |
|---|---|
| Colour Tone Criterion | Brown, deep brown, bright brown, green brown |
| Location Criterion | In the vicinity of ridge lines, road sides, and the cut-off side of a river channel |
| Shape Criterion | Lenticular-shaped or spoon-shaped, or cumulated as tree-shaped in river basins, or a triangular or rectangular-shape if located near river banks |
| Direction Criterion | The longitudinal axis is in the direction of gravity or perpendicular to flow-lines |
| Shadow Criterion | Shadows are applied to assist the interpreter to percept river bottoms and ridges in 2D images |

Table 1 rules of interpretation for landslides

The rules of interpretation for landslides in Table 1 are to be implemented as computing algorithms for automatic identification. For example, the colour tone of a new landslide is usually an expression of bare lands with unique spectral signature. NDVI (Normalized Vegetation Index) is one of the 20 vegetation indices, useful for this purpose. Equation of NDVI is as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

This index is derived from the reflectance of red band and NIR band. It is also an indicator of biomass. The value of NDVI is in the range of –1 and +1. A negative value designates a bare land.

The location criterion of a landslide can be realized by using DTM (Digital Terrain Model) for generating a ridgeline and by digitising roads from the 1:5000 orthophoto maps, which are the most common maps in Taiwan. Subsequently, a vicinity analysis can be implemented.

The direction criterion is implemented by intersection operation of the ridgelines and buffer zones generated by river-lines.

The shape criterion and shadow criterion are not implemented in this study. However, slope criterion is added. Statistics shows that highest possibility of landslides take place on slopes of 15°~30°, and then on slopes of 30°~45° (Hsiao et. al., 2003).

A synergy of satellite images, DTM, existing roads, and drainage lines is better implemented in a neural network system as adopted in this study. A scoring scheme is used to transform the above-mentioned criteria into the neurons of input layer of the artificial neural network as shown in Table 2.

| Colour Criterion | | Direction Criterion | | Location Criterion (Ridge line) | |
|---|---|---|---|---|---|
| NDVI Value | Score | Buffer size | Score | Buffer size | Score |
| < 0.0 | 1.0 | < 50 m | 1.0 | < 50 m | 1.0 |
| 0.0~0.25 | 0.8 | 50~100 | 0.8 | 50~100 | 0.8 |
| 0.25~0.5 | 0.6 | 100~150 | 0.6 | 100~150 | 0.6 |
| 0.5~0.75 | 0.4 | 150~200 | 0.4 | 150~200 | 0.4 |

| | | | | | |
|---|---|---|---|---|---|
| 0.75~1.0 | 0.2 | 200~250 | 0.2 | 200~250 | 0.2 |
| Location Criterion (Roads) | | Slope (1) | | Slope (2) | |
| Buffer size | Score | SLOPE value | Score | SLOPE value | Score |
| < 50 m | 1.0 | < 5° | 0.0 | 60°~75° | 0.0 |
| 50~100 | 0.8 | 5°~15° | 0.09 | >75° | 0.0 |
| 100~150 | 0.6 | 15°~30° | 0.52 | | |
| 150~200 | 0.4 | 30°~45° | 0.35 | | |
| 200~250 | 0.2 | 45°~60° | 0.04 | | |

Table 2 Interpretation Criteria

### 2.3 An Artificial Neural Network (ANN) Classifier

An Artificial Neural Network (ANN) is a simulation of the functioning of the human nervous system that produces the required response to input (Robert, 1990). ANN is able to provide some of the human characteristics of problem-solving ability that are difficult to simulate using logical, analytical techniques. One of the advantages of using ANN is that it doesn't need a predefined knowledge base. ANN can learn associative patterns and approximate the functional relationship between a set of input and output. A well-trained ANN, for example, may be able to discern, with a high degree of consistency, patterns that human experts would miss. In a neural network, the fundamental variables are the set of connection weights. A network is highly interconnected and consists of many neurons that perform parallel computations. Each neuron is linked to other neurons with varying coefficients of connectivity that represent the weights (sometime is refereed as strengths in other literature) of these connections. Learning by the network is accomplished by adjusting these weights to produce appropriate output through training examples fed to the network (Zurada, 1992).

The multilayer perceptron (MLP) is one of the most widely implemented neural network topologies. The article by Lippman is probably one of the best references for the computational capabilities of MLPs. Generally speaking, for static pattern classification, the MLP with two hidden layers is a universal pattern classifier. In other words, the discriminant functions can take any shape, as required by the input data clusters. Moreover, when the weights are properly normalized and the output classes are normalized to 0/1, the MLP achieves the performance of the maximum a posteriori receiver, which is optimal from a classification point of view. In terms of mapping abilities, the MLP is believed to be capable of approximating arbitrary functions. This has been important in the study of nonlinear dynamics, and other function mapping problems. The MLPs are trained with error correction learning, which means that the desired response for the system must be known, as well known as backpropagation algorithm (Zurada, 1992). The objective of learning is to minimize the error (RMS in this case) between the predicted output and the known output.

An MLP type neural network model was utilized in this work using NeuroSolutions 4.24 software (NeuroDimension, 2004) developed by NeuroDimension, Inc. The architecture of a network that consists of (a) one input layer that contains 4 input variables, (b) one hidden layer of 5 nodes, (c) one output layer that contains 1 output variable, and (d) connection weights that connect all layers together.

There are two important parameters including a learning rate coefficient (Eta) and a momentum factor (Alpha) during training. In general, Eta's valid range is between 0.0 and 1.0. Although a higher Eta provides faster learning, it can also lead to instability and divergence. A small Eta offers improved numerical convergence, however training time is greatly increased. When a new ANN training is initiated, the user must provide a starting Eta value. It is advisable to start with a small number because it is conservative. When a value in the range of 0.001 to 0.1 is used, it normally starts a smooth training process without the risk of divergence.

The Alpha damps high frequency weight changes and helps with overall algorithm stability, while promoting faster learning. For most of the networks, Alphas are in the range of 0.8 to 0.9. However, there is no definitive rule regarding Alpha. Higher momentum values (between 0.8 and 0.9) are most commonly used since the damping effect usually helps training characteristics. If training problems occur with a given alpha value, different values can be tried. In NeuroSolutions, the user can define this parameter. After several times of test, the alpha value is set to be 0.7 in this study.

The transfer function for PEs serves the purpose of controlling the signal strength for its output. The input for the transfer function is the dot product of all PEs' input signals and weight vectors of the PE. The four commonly used transfer functions are the Sigmoid, Gaussian, Hyperbolic Tangent and Hyperbolic Secant. In general, the Sigmoid function $\{1/(1+e^{-x})\}$ will produce the most accurate model, but the learning rate will be slower as compared to other functions. The Sigmoid function acts as an output gate that can be either opened at 1 or closed at 0. Since the function is continuous, it allows the gate to be opened partially (any value between 0 and 1). Hyperbolic Tangent is selected as the transfer function in this study.

Cross validation is a highly recommended method for stopping network training in the NeuroSolutions. This method monitors the error on an independent set of data and stops training when this error begins to increase. This is considered to be the point of best generalization. The testing set is used to test the performance of the network. Once the network is trained the weights are then frozen, the testing set is fed into the network and the network output is compared with the desired output. Twenty percentage of training data is used to be a cross validation and test dataset in this work.

## 3. CASE STUDY AND DISCUSSIONS

### 3.1 Test datasets and Pre-processing

Jiu-fen-ell mountain is selected as the test area, which is a typical area of landslides especially after by the big shock of the Chi-Chi earthquake at Nantou County of central Taiwan on 1999/09/21. Datasets collected for this study include Quickbird images, digital vector maps including river lines and roads obtained from 1:5000 photomaps, DTM, and airborne LIDAR data (Shih, 2002).

Quickbird images are registered to the vector datasets by using image-to-map function of ENVI 3.5, which is applying an affine transformation as shown in Figure 1, where the false color image is a composite of bands NIR, G, and B. Roads are designated as yellow colour and river as blue colour.

NDVI for colour tone criterion is executed using the function TRANSFORM>NDVI of ENVI 3.5, as shown in Figure 2.

Digital Elevation Model (DEM) of the study area is abstracted from airborne LIDAR data, retrieved by a Fortran program developed by the authors, to match with the satellite image. Thus, regular DEM is generated by interpolation of inverse distance and used for generating ridge-lines and slope gradients.

The criteria of location and direction are fulfilled by synergizing these results.

### 3.2 Results

The area size of the test area is in 1229x1209 pixels with pixel size of 2.44 m. A correlation analysis is carried out for the four factors, namely NDVI, slope, direction, and locations (Table 3). As indicated in Table 3, correlation coefficients are very low in general except V3 and V4 with a coefficient of 0.19. The highest value of correlation with the target V5 is colour tone V1 with a value of 0.25; and then the slope V2. Principle component analysis is also applied to extract 4 components, and thus to reduce the correlation between factors. The relation between factors and the targets are also reduced accordingly. Therefore, the components are not adopted for the input of neural network. Subsequently, information obtained by visual interpretation as shown in Figure 4. is used to extract inputs of neural network by extracting 5%, 10%, 15%, 20%, and 25% of data. Under 4-6-1 neural network structure, various subsets of random samples apply on 1000 training cycles. Learning errors for ANN training are shown in Table 4. The MSE (Mean Square Error) is higher than the threshold of 0.1 required by ANN. The correlation coefficient is 0.64, indicating that input datasets are not highly correlated with the targets. So many as 1000 training cycles are applied to observing learning error curve to see whether it is possible to reduce the MSE to as low as 0.1. As shown in Figure 5, after 100 training cycles the network becomes stable. Classification is further conducted using the trained network as shown in Table 5. A successful rate of classification is 85% for landslide and 73% for non-landslide. The omission and commission error are 0.27 and 0.15, respectively. The accuracy could be affected by following factors:

a. The criteria for visual interpretation are not suitable for ANN in terms of the correlation between the factors and the target. Part of the reason may be attributed to the mismatch of the date of various information sources such as Quickbird images were taken on 15 Jan 2003; the LIDAR point clouds, in May 2002; digital vectors, in August 2002; the landslides, in 1999. Evidence is given by that the NDVI of manually-interpretated landslide area was as high as 0.25, indicating the area is vegetated other than bare.

b. Selected signatures are not good enough to represent the features as required. Criteria for manual interpretation such as the cut-off slopes and others are not implemented in this study.

| | Correlation between Vectors of Values | | | | |
|---|---|---|---|---|---|
| | V1 | V2 | V3 | V4 | V5 |
| V1 | 1.000 | .013 | .012 | .009 | .230 |
| V2 | .013 | 1.000 | -.044 | .011 | .087 |
| V3 | .012 | -.044 | 1.000 | .161 | -.010 |
| V4 | .009 | .011 | .161 | 1.000 | .002 |
| V5 | .230 | .087 | -.010 | .002 | 1.000 |

Table 3. Correlation between four signatures and target.

| (a) 5% samples | | (b) 10% samples | |
|---|---|---|---|
| MSE | 0.46 | MSE | 0.44 |
| ERROR(%) | 13.8 | ERROR(%) | 13.0 |
| r | 0.62 | r | 0.64 |
| (c) 15% samples | | (d) 20% samples | |
| MSE | 0.39 | MSE | 0.41 |
| ERROR(%) | 11.6 | ERROR(%) | 12.3 |
| r | 0.68 | r | 0.67 |
| (e) 25% samples | | (f) all samples | |
| MSE | 0.38 | MSE | 0.51 |
| ERROR(%) | 11.2 | ERROR(%) | 14.8 |
| r | 0.70 | r | 0.55 |

Table 4. Learning errors for ANN training

| (a) 5% | landslide | Non- | (b) 10% | landslide | Non- |
|---|---|---|---|---|---|
| landslide | 84% | 16% | landslide | 81% | 19% |
| Non- | 28% | 72% | Non- | 23% | 77% |
| (c) 15% | landslide | Non- | (d) 20% | landslide | Non- |
| landslide | 85% | 15% | landslide | 86% | 14% |
| Non- | 21% | 79% | Non- | 23% | 77% |
| (e) 25% | landslide | Non- | (f) all | landslide | Non- |
| landslide | 86% | 14% | landslide | 88% | 12% |
| Non- | 22% | 78% | Non- | 45% | 55% |

Table 5. Accuracy for ANN Training

When the pixels with NDVI larger than 0.25 are filtered out for the area according to manually-interpretated landslides. Result shows that the correlation between colour tone and the target is raised to 0.47. With this condition, the MSE becomes accepted with a value smaller than 0.1 in a new ANN training cycle. And the correlation between the factor and the target becomes 0.75. However, the accuracy of non-landslide is not improved.

## 4. CONCLUSIONS

Some of the criteria for manual interpretation such as shape criterion and shadow criterion have not been implemented in this study due to inadequacy of information. This can be the reason that the final successful rate of identification of landslide is only 85%. Further research is required to improve both the spatial analysis algorithm and the data sources. Nevertheless, some findings are concluded in this study.

1. It is feasible to gain a synergy of information on high resolution images, digital terrain models, existing roads and drainage systems and automate the information for landslide identification.
2. The correlation analysis of the four criteria for manual interpretation shows that only direction and location criteria are correlated. And, only colour tone criterion is better correlated with the target.
3. Under 4-6-1 ANN network structure, the MSE is 0.43 after training cycles, not acceptable to the threshold of 0.1. Furthermore, a correlation coefficient of 0.64 indicates that the neurons and the targets are not highly correlated. These could be due to the mismatch of the date of various data sources.
4. Result of the classification shows a successful rate of 85% for landslide and 75% for non-landslide. The omission and commission error is 0.27 and 0.15, respectively。
5. As shown in this study, GIS functions such as buffering, spatial intersection, overlay, and terrain analysis are employed. A system for landslide interpretation would require capabilities both from a GIS and an image analysis system.

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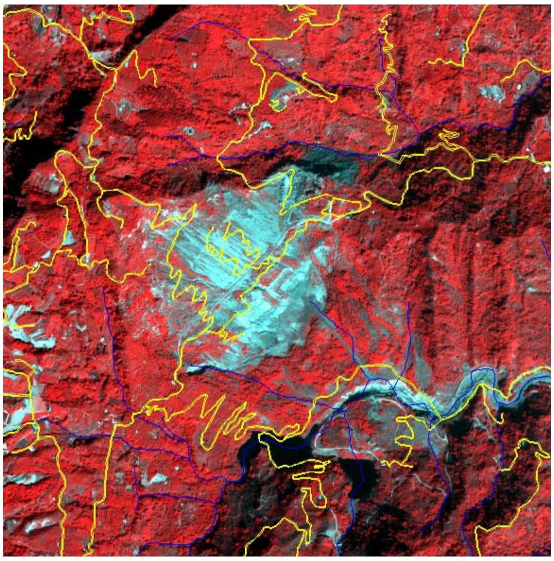

Figure 1. Quickbird image as registered on vector rivers and roads.

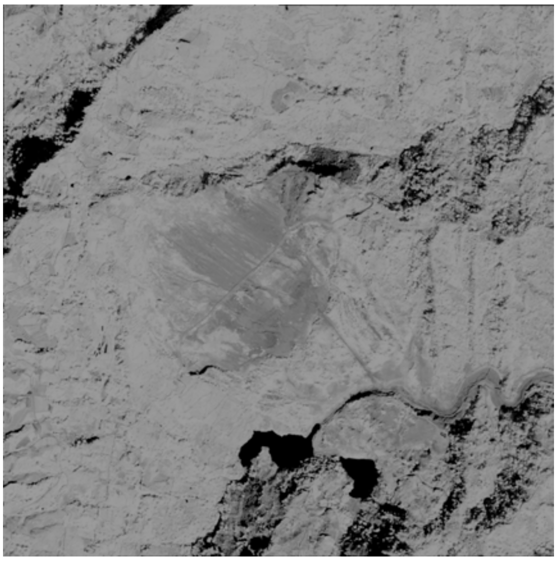

Figure 2. NDVI image of the study area.

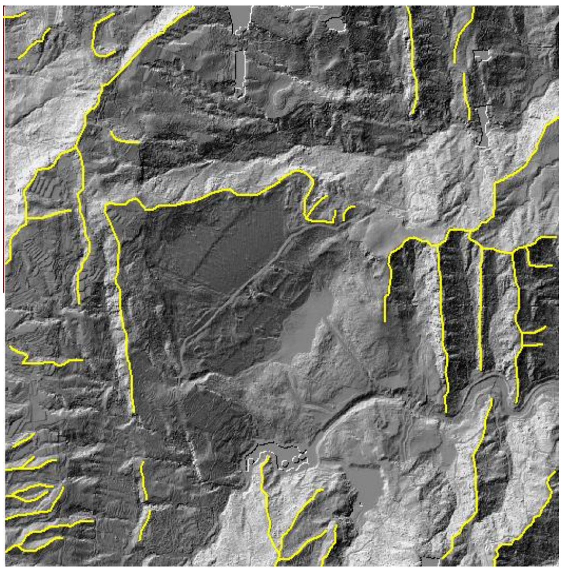

Figure 3. Hillsheded relief overlaid with ridge lines.

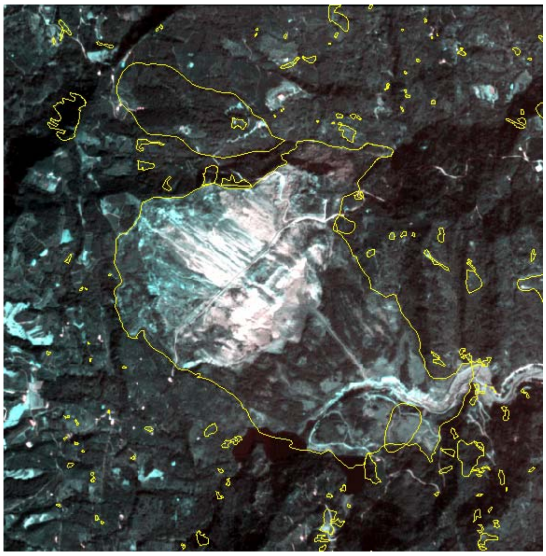

Figure 4. The landslides map obtained by visual interpretation.

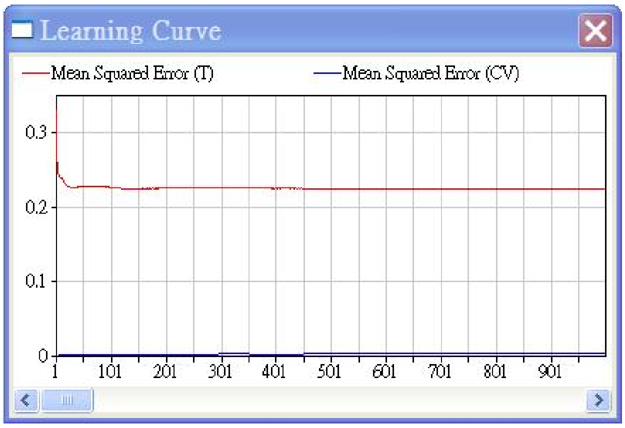


Figure 5. ANN learning curve